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New Method for Multiple Cues Fusion Combined DST with DSmT

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Abstract: DST (Dempster-Shafer theory) involves some counter-intuitive behaviors when multiple evidences conflict highly. DSmT (Dezert-smarandache theory) can solve this problem. Under increment of focal target elements, high computation cost has blocked the wide application of DSmT. To solve this problem, some modified combination rules have been proposed in literature. In this study, an adaptive integration method based on DST and DSmT was presented. To make a reasonable choice, a parameter measuring conflict degree called evidence distance is defined to determine. Threshold value is evaluated by product of conflicting factor and evidence distance. When conflict is smaller than the threshold value, DST is used to fuse. While conflict is larger, DSmT is used to fuse until the conflicting rate value is smaller than the threshold value. To illustrate effectiveness and good performance of new method, some methods are compared. Reliable result with low cost computation can be obtained by new method. Results indicate that this method can highlight the effectiveness of fusion. It synthesizes merits of DST and DSmT. New method is more reasonable than others.

Key words: Dempster-shafer theory, dezert-smarandache theory, adaptive integration fusion method, evidence distance, conflict factor

INTRODUCTION

DST classic combination rule is effective to fuse multiple sources of evidences. Although Shafer's seminal work for information fusion, many scholars in this research field have founded some limitations (Zadeh, 1979; Yager, 1987, 1997; Smets, 2007). Fusion result is unreasonable by DST when evidences highly conflict. Scholars proposed many alternatives to improve the validity. DSmT can fuse multiple cues of uncertain and conflicting beliefs. But high computation cost of DSmT blocked its wide application. The fusion result is under to DST in low conflict situation. To solve this problem, an adaptive integration fusion method combining DST with DSmT was proposed in this study. Scholars in this research field had used some methods (Zhou, 2009; Hou *et al*., 2006; Wang *et al*., 2011; Li *et al*., 2010). Results indicate these methods had limitations. Making a reasonable choice of the threshold is key problem. Conflicting factor can not describe conflicting degree completely (Liu *et al*., 2009). In this study, threshold value is evaluated by product of conflicting factor and evidence distance. Reliable result with relate low cost computation can be obtained by new method. Results provided reliable information to improve the recognition capability using the proposed method.

MATERIALS AND METHODS

Materials of DST: DST establishes the definitions of discernment frame and power set denoted Θ and 2^{Θ} respectively. The conditions the Basic Probability Assignment (BPA) should fulfill and the definitions such as belief and plausibility function can be easily founded in studies of related research field conducted (Shafer, 1976). DST is regarded as an efficient theory because it can use orthogonal sum to fuse multiple BPAs of sources of evidences (Smarandache and Dezert, 2006). The combination rule of DST is defined as:

$$m(A)=\begin{cases}\dfrac{\sum_{A_i\cap B_j=A} m_1(A_i)m(B_j)}{1-K} & (A\neq\varnothing)\\ 0 & (A=\varnothing)\end{cases} \tag{1}$$

$$K=\sum_{A_i\cap B_j=\varnothing} m_1(A_i)m_2(B_j)<1 \tag{2}$$

where, K is a measure of conflict between multiple sources. The denominator 1-K is addressed as a normalization factor. A and B are focal target elements. The larger K is, the higher the conflict of sources between evidences is (George and Pal, 1996). If K = 1, the orthogonal rule fails to use. Commutativity and

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associativity are two properties of the orthogonal combination rule should fulfill. The belief and plausibility functions are defined as:

$$\mathrm{Bel}(A)=\sum_{B\subset A} m(B) \tag{3}$$

$$\mathrm{PL}(A)=1-\mathrm{BEL}(\overline{A})=\sum_{B\cap A\neq\varnothing} m(B) \tag{4}$$

where, $\overline{A}$ is the complementary of A. Belief and plausibility functions reflect the minimum and maximum uncertainty value, respectively.

Materials of DSmT: Belief function $\mathrm{Bel}_1(\bullet)$ and $\mathrm{Bel}_2(\bullet)$ of the free DSm model $M^f(\Theta)$ correspond to the conjunctive consesus of multiple sources (Smarandache and Dezert, 2006). Equation of the classic DSm combination rule is given by:

$$\forall C\in D^{\Theta},\ m(C)=\sum_{A,B\in D^{\Theta},A\cap B=C} m_1(A)m_2(A) \tag{5}$$

DSmT is the theory of reasoning with plausible and paradoxical sources of evidences, which is regarded as the extension or generalization of DST in literature (Sun and Bentabet, 2010). DSmT establishes on definitions of general discernment frame and hyper-power set. Discernment frame Θ of DST is considered as a set of exclusive elements. While the hyper-power set D^{Θ} is considered as a set for all hypotheses obtained from Θ with $\cup$ and $\cap$ operators in DsmT. DsmT includes 5 Proportional Conflict Redistribution (PCR) rules. Although PCR5 rule is considered as the most efficient rule, it is with high computation cost in implementation. The PCR5 equation for combination (s = 2) is given by:

$$m_{pcr5}(X)=\sum_{X_1,X_2\in D^{\Theta},X_1\cap X_2=X} m_1(X_1)m_2(X_2)+\sum_{Y\in D^{\Theta}\setminus\{X\},X\cap Y=\varnothing}\left[\frac{m_1(X)^2 m_2(Y)}{m_1(X)+m_2(Y)}+\frac{m_2(X)^2 m_1(Y)}{m_2(X)+m_1(Y)}\right] \tag{6}$$

ADAPTIVE INTEGRATION METHOD BASED ON DST AND DSmT

Adaptive integration method for static fusion situations: DST and DSmT have merits and limitations of their own, respectively. When the conflict is low between sources, DST is with low computation cost and can obtain reasonable result. PCR5 of DSmT is the most efficient rule (Smarandache and Dezert, 2011). But it is relative complex in implementation. With the increasing demand for a reasonable fusion result with relative simple implementation process, it is required to use a new method to combine the merits of DST and DSmT. Conflict factor is a measure of conflict between sources of evidences. But it is unreasonable only on basis of the value of conflict factor. Zhang *et al.* (2001) presented the defination of conflicting rate, which can measure the degree of conflicting between sources of evidences. The computation equation is given as follows:

$$\delta=\frac{\sum_{B_i\cap C_j=\varnothing} m_1(B_i)m_2(C_j)}{\sum_{B_i\cap C_j=\varnothing} m_1(B_i)m_2(C_j)+\sum_{A\subseteq U} m_1(A)m_2(A)} \tag{7}$$

But the convergence rate is slow. With the aim to obtain a reasonable result with relative simple implementation process, key step is selection of the threshold. In fact, the value of the threshold of different soureces should be different. It may be one dot or more dots. And it may be a interval. For the convenience of the implementation, When the conflict is smaller than the threshold value, the classic combination rule of DST is used to fuse the multiple cues. While the conflict is larger than the threshold value, PCR5 of DSmT is used to fuse until the conflicting rate value is smaller than the threshold value.

Measurement of the threshold based on conflicting factor and evidence distance: Conflicting factor can represent the size of conflict, but it can not denote if the evidences are conflict or not (Liu *et al.*, 2009). Conflict factor and evidence distance being used sepatately can't describe the conflicting degree completely. Given the example as follows:

$$\Theta=\{\theta_1,\theta_2,\theta_3\}$$
$$m_1(\theta_1)=0.6\ m_1(\theta_2)=0.3\ m_1(\theta_3)=0.1$$
$$m_2(\theta_1)=0.6\ m_2(\theta_2)=0.3\ m_2(\theta_3)=0.1$$

Two evidences above are same. The conflict between them is zero by intuition. But the conflict factor k = 0.54 by caculation. The evidence distance d = 0, it is in accord with the result through analysis. Conflicting factor and evidence distance is complementary. So, the combination of conflict factor with evidence distance is used to determine the conflicting degree in this study. The defination of evidence distance is given as follows:

$$d(m_1,m_2)=\sqrt{\frac{1}{2}\left(\overrightarrow{m_1}-\overrightarrow{m_2}\right)^T \underline{\underline{D}}\left(\overrightarrow{m_1}-\overrightarrow{m_2}\right)}$$

$$\underline{\underline{D}}[i,j]=|A_i\cap B_j|/|A_i\cup B_j| \tag{8}$$

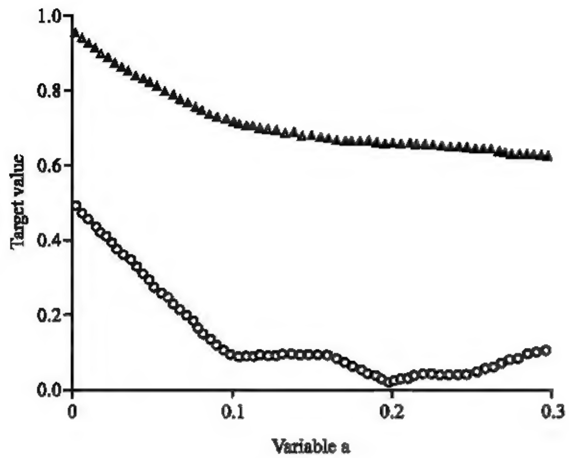

Fig. 1: Variation curve of k and kd with respect to variable ak is conflict factor, kd is product of conflict factor and evidence distance, a is a variable

where, $\underline{\underline{D}}$ is $2^{|\Theta|}\times 2^{|\Theta|}$ positive definite matrix. Elements A_i, B_j are the elements of power set 2^{Θ}. Combination of conflict factor with evidence distance is given by:

$$kd = \sum_{B,C\in D^{\Theta},B\cap C=\varnothing} m_1(B)m_2(C)\bullet d(m_1,m_2) \quad (9)$$

The more evidences work for the same basic principle.

Let's consider an example where $\Theta = (\theta_1, \theta_2, \theta_3)$ and two independent evidences provide the mass functions are as follows:

$$m_1(\theta_1) = 0.9\text{-}2a, m_1(\theta_2) = 0.06+a,$$
$$m_1(\theta_3) = 0.04+a;$$
$$m_2(\theta_1) = a, m_2(\theta_2) = 0.2+2a$$
$$m_2(\theta_3) = 0.8\text{-}3a$$

where, $0<a<0.2667$, take 0.006 as the step leng, picture with k curve and kd curve is as follows.

It can be easily seen from Fig. 1. Inflection point did not appear in k curve. The inflection point appears at a = 0.128 and a = 0.198 in kd curve, but the slope alteration is conspicuous when a = 0.128. This dot is the target inflection point. So, when $0<a<0.128$, DSmT is used to fuse, when $0.128<a<0.2667$, DST is used to fuse. In order to show the efficiency of new method in this study, Let a = 0.1, fusion results in different methods is as follows.

It can be seen from Table 1 easily. Bpa of $m(\theta_1)$ and $m(\theta_3)$ in Yager (1987, 1997) and Smets (2007) method is 0.07. It can not draw a clear conclusion from this value.

Table 1: Basic probability assignments of $m(\phi)$, $m(\theta_1)$, $m(\theta_2)$, $m(\theta_3)$, $m(\Theta)$ based on rules of DST, Yager, Murphy, Smets and new method in this study

Fusion method	Bpa of $m(\phi)$	Bpa of $m(\theta_1)$	Bpa of $m(\theta_2)$	Bpa of $m(\theta_3)$	Bpa of $m(\Theta)$
Dempster-shafer theory		Can't use to fuse			
Yager's rule	0	0.0700	0.0640	0.0700	0.796
Murphy's rule	0	0.4000	0.2800	0.3200	0
Smets's rule	0.796	0.0700	0.0640	0.0700	0
New method	0	0.4644	0.2559	0.2991	0

Bpa of $m(\theta_1)$ in Murphy method is 0.4, it is not obvious to conclude, but the Bpa of $m(\theta_1)$ in new method proposed in this study reach 0.4644, it is obvious to conclude (θ_1) is the target element. Realiable result with relate low cost computation is obtained by new method.

CONCLUSION

DST and DSmT have their own merits and limitations respectively. Conflicting factor can represent the size of conflict, but it can not denote if the evidences are conflict or not. Conflict factor and evidence distance being used sepatately can't describe the conflicting degree completely. In this study, a new adaptive integration method was proposed based on DST and DSmT for fusion problem. It makes the choice of threshold more effective combining conflict factor with evidence distance to denote the conflict degree. It makes the fusion result more reliable with relative low computation cost. This method has its value from theoretical and practical point of view. It could serve as a useful method to solve practical problem.

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REFERENCES

George, T. and N.R. Pal, 1996. Quantification of conflict in Dumpster-Shafer framework: A new approach. Int. J. General Syst., 24: 407-423.

Hou, J., Z. Miao and Q. Pan, 2006. A adaptive integration algorithms with DST and DSmT. Microelectronics Comput., 23: 150-152.

Li, P., X.H. Huang and M. Wang, 2010. Adaptive universal proportional redistribution rule under DSmT framework. Comput. Eng. Appl., 6: 16-18.

Liu, Z.G., Y.M. Cheng, Q. Pan and Z. Miao, 2009. Combination of weighted belief functions based on evidence distance and conflicting belief. Control Theory Appl., 12: 1439-1442.

Shafer, G., 1976. A Mathematical Theory of Evidence. Princeton University Press, Princeton, USA.,.

Smarandache, F. and J. Dezert, 2006. Advances and Applications of DSmT for Information Fusion: Collected Works. Vol. 3, American Research Press, Washington, DC., USA., pp: 73-75.

Smarandache, F. and J. Dezert, 2011. Uniform and partially uniform redistribution rules. Int. J. Uncert. Fuz. Knowl. Based Syst., 19: 921-937.

Smets, P., 2007. Analyzing the combination of conflicting belief functions. Inform. Fusion, 8: 387-412.

Sun, Y. and L. Bentabet, 2010. A particle filtering and DSmT based approach for conflict resolving in case of target tracking with multiple cues. J. Math. Imag. Vis., 36: 159-167.

Wang, Q., W. Wang and M. Wu, 2011. Adaptive information-iusion algorithm of DST and DSmT. Ordnance Ind. Automation, 2: 41-43.

Yager, R.R., 1987. Using approximate reasoning to represent default knowledge. Artif. Intell., 31: 99-112.

Yager, R.R., 1997. A general approach to the fusion of imprecise information. Int. J. Intell. Syst., 12: 1-29.

Zadeh, L., 1979. On the Validity of Dumpster's Rule of Combination. Electronics Research Laboratory, University of California, California, Pages: 24.

Zhang, S.Y., P. Quan and Z. Hong-Cai, 2001. Conflict problem of dempster-shafer evidence theory. Aeronautica Et Astronautica Sinica, 22: 369-372.

Zhou, X.Y., 2009. Study on the threshold of combining DST and DSmT. Ship Electronic Eng., 12: 128-141.